Bulgarian Journal of Agricultural Science, 23 (No 6) 2017, 887–893
Agricultural Academy

IDENTIFICATION OF FREIGHT PATTERNS VIA ASSOCIATION RULES: THE CASE OF AGRICULTURAL GRAINS

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Abstract

Moreira, C. E. S., A. L. R. de Oliveira, S. R. de M. Oliveira and A. Yamakami, 2017. Identification of freight patterns via association rules: the case of agricultural grains. *Bulg. J. Agric. Sci.*, 23 (6): 887–893

The road system is the main form of transport in the biggest production regions between the domestic market and exporting ports, as well as the transport used on intermodal routes connecting production areas with rail and/or water terminals. The goal of the current study is to recognize non-obvious patterns in a mass of data for road freights of selected grain: soy and corn. As such, the data mining technique, known as the *Apriori* algorithm, is used to generate association rules that describe such patterns. Among the varied rules identified by this technique, we highlight those that enable us to conclude that: i. Soy and corn production in the state of Mato Grosso is carried via the port of Santos; ii. The grain storage silos located in the state of Mato Grosso mainly receive shipments from the same state; iii. The port of São Francisco do Sul, mainly receives corn; iv. In the state of Minas Gerais there is an intermodal route that receives the grain originating mostly from Mato Grosso and transfers it to the rail system, which then carries the load to its next destination.

Key words: agribusiness; data mining; logistics; transport

Introduction

Brazil is the main agricultural powerhouse of the world, with its 58.3 million hectares of cultivated land producing 186.4 million tons of grain (CONAB, 2016). This massive volume of grain needs to be carried out in an agile manner and at the lowest possible transport cost, minimizing the associated logistics costs. However, in a country with continental dimensions, which mostly employs the road system in shipping cargo, constant monitoring and perfecting of employed logistics techniques is required.

In this context and intent on making use of the ideal transport routes, the agricultural products freight has become a widely studied area in which a large volume of data has been collected. As such, the application of data mining tasks is very appropriate, since there are patterns to be identified, for example, making forecasts about the lowest price of freights. As for the forecasts, freight estimates may be conducted for new and/or unknown routes that may be cheaper and/or faster than the traditionally travelled routes.

Cargo transport in Brazil is no longer of secondary importance, it now plays a major role in planning and strategic decision making of countless organizations, especially those linked with agribusiness (Oliveira, 2006). Agricultural grains, especially soy and corn, are examples of these. Spatial changes in their production regions or agricultural frontiers point to the need for studies whose main goal is to optimize the available logistics distribution in an attempt to

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reduce costs, thus enabling an increase in the international competitiveness of grains.

The road system is the main form of transport in the main production areas between the domestic market and the exporting ports, as well as the transport used on intermodal routes connecting the production areas with the rail and/or water transport terminals.

As such, the knowledge of road freight behavior is an important support tool for decision making, as it contributes relevant information on market prices based on the characteristics of each operation and the varying services rendered by the transporters.

Since the cost of road transportation forms a large share of the price of grain, to maintain its competitiveness in the world markets, the national productive sector needs to seek ways to reduce its logistics costs. These reductions may result from partnerships with transport companies for the constant monitoring of the transport networks. Besides, information relating to the identification of alternative routes, the evaluation of the use of current routes, the discovery of new trends and transport technologies, based on recent history and the present scenario, may help the area managers in decision making. These may potentially be extracted from a data bank using data mining techniques, especially from the Mining of Association Rules.

The current study employs a data mining technique to identify non-obvious patterns in a database describing the freight of soy and corn grains exclusively on national routes. For this job, the *Apriori* algorithm was selected (Agrawal, et al., 1993; Agrawal and Srikant 1994; Liu et al., 1998), which is capable of generating rules of association from a data bank. This technique functions mainly by making use of two parameters: a. support, frequency of pattern occurrence in the whole base; b. confidence, measured as the strength of the rules.

Materials and Methods

Data Mining is comprised of a series of techniques, such as statistics, probabilities, and artificial intelligence, capable of answering several questions or even discovering new information in big data banks.

Several Data Mining techniques are available in the literature (Chen et al., 1996; Cheung et al., 1996). One of the most attractive techniques is the Mining of Rules of Association, where the *Apriori* algorithm stands out. It can work with a large number of attributes, generating several combinatory alternatives among them. The *Apriori* algorithm conducts successive searches in the entire data base, maintaining optimal performance in terms of processing time (Agrawal and Srikant, 1994).

Frequently, in big data banks that store thousands of items, such as those existing in supermarket chains, the goal is to discover important associations among the sold items, so that the presence of a few of these in a transaction (purchase or sale) implies the presence of others in the same transaction. The goal is to find all the relevant rules of association between the items of type X (preceding) $\Rightarrow$ Y (consequent), in a data bank of t transactions.

The process for extracting rules of association was initially presented by Agrawal et al. (1993) as a technique that finds relations among the occurrence of items in transactions of a data base. Where $I = \{i_1,\ldots, i_n\}$ is a set of literals, called items. A set $X \subseteq I$ is called an *itemset*. An itemset X with k elements is called an *itemset*_k. D is a database with t transactions that involve elements that are a subset of I. The transaction t supports an *itemset* X if $X \subseteq t$. A rule of association is an expression of the form $X \rightarrow Y$, where X and Y are *itemsets*. Support of the rule is the fraction of the number of transactions that contain $X \cup Y$ in D. Confidence is the fraction of the number of transactions containing X that also contain Y. A well-known example of the rule of association involving data from a shopping basket is that "70% of the orders that contain diapers also contain beer; and 4% of all orders contain both items". In that example, 70% is the confidence of the rule and 4% is the support of the rule. The problem of mining rules of association consists of finding strong rules, which are the rules that satisfy the restrictions of minimum support and minimum trust specified by the user.

Data presentation

The information on road routes for grains and their respective freight costs that compose the data mass used in this study were obtained from the Freight Information System (SIFRECA, 2016). These have the attributes presented in Table 1, where: YEAR, is the year in which the price of that route was increased and can take on figures from the set {2013, 2014, 2015}; MONTH is the month in which the price of that route was obtained; PRODUCT describes the grain carried on that route and can be corn or soy; ORIGIN is the city of origin of the load; UFORIGIN is the symbol of the destination state of the cargo; R$/t.km is the price per ton per kilometer driven on that route; Distance (km) in kilometers is the distance travelled by the truck between the origin and the destination; and R$/t is the price charged for transporting a ton of grain along the selected route.

The UF Origin and UF Destination columns – means the Brazilian State where the city is located. A total of 19341 transport routes were analyzed, out of which 2760 were travelled in 2013, 2556 in 2014, and 14025 in 2015. Regarding product share, 9713 were soy transport routes and 9628 were corn transport routes

Table 1
Raw data bank and attributes describing the transport routes

Year	Month	Product	City Origin	UF Origin	City Destination	UF Destination	Distance, km	Freight, R$/t	Index, R$/t.km
2013	April	Soy	Sorriso	MT	Santos	SP	2211	286.75	0.129
2013	April	Soy	Sinop	MT	Santos	SP	2294	287.33	0.125
2013	July	Corn	Rio Verde	GO	Paranaguá	PR	1378	115.00	0.083
2013	July	Corn	Rio Verde	GO	Santos	SP	1002	145.00	0.144

Data preparation

According to Pyle (1999), the data preparation stage is the longest data mining stage, since it involves steps that go from identifying the problem until the modelling, formulation, and presenting of results. Pyle (1999) mentions that, in order to be successful in the data preparation stage, about 60% of total time invested in the mining process must exclusively be dedicated to this stage.

In fact, throughout this study, this statement was easily verified. The data preparation stage was consistently the one taking up most amount of time and demanding the most concentrated efforts so that in the end it was possible to obtain a set of robust and consistent data, from which interesting rules of association could be generated. The preparation of freight data was divided into four sub-stages: I. filling in blank figures; II. data cleaning; III. reduction and dimensionality; and IV. discretization of numeric attributes. In what follows, each of these stages is described.

The set of data obtained from the SIFRECA (2016), although being well designed for the years 2013 and 2014 in the year 2015, precisely the year with most number of observations, did not present any information regarding the distance between the points of origin and the points of destination of the route and instead presented just freight figures. The information on distance, when it comes to valuing the transport, is indispensable information for any model, be it descriptive, as in the case of rules of association, or predictive.

The problem was partly solved by sweeping the routes from previous years, for each origin and destination presented in 2015, and copying that figure for the most recent year. At the end of this process that was automated, we were still short of distance information on a few routes (about 14000). Finally, we chose to fill in the remaining figures with the distance given by API from GoogleMaps (GoogleMaps, 2016), which gives us, among other information, all the possible routes between the two selected cities and their respective distances. Thus, an algorithm was created to automate communication with the GoogleMaps service to obtain information on the cities along the route and extraction of the route's distance. In the cases where more than one route was indicated, the route with the median distance was recorded.

Having solved the issue of missing figures, we went ahead with data cleaning. Even after filling in the missing distances automatically, some could not be reached, either due to being named after cooperatives, and therefore not being located by GoogleMaps, or due to errors in typing the city's name or because they were named after farms or districts, which could also not be found. These, which came to a very small amount, compared with the total data obtained (less than 100 instances) were removed together with their respective instances. The instances where the R$/t attribute had a figure between 1.00 and 2.00 were also removed, because it was soon verified that such figures for a ton of grain were unreal and therefore contained errors, possibly introduced during the data collection or digitalization stages.

There was also a stage of dimensionality reduction that did not use any algorithm rather used only concepts for detecting redundancy and diminishing cardinality.

The attribute that suggested a removal with greater clarity was the Index (R$/t.km, price per ton, per kilometer travelled) because this could be measured as a function of two other attributes – distance (km) and freight cost (R$/t) – thus representing a redundancy.

The attributes that represented the names of cities of freight origin and destination, Origin and Destination, were also removed. These presented a very high cardinality (in final instance, equal to the number of cities in Brazil), which resulted in an extremely high level of rules of association (more than double the quantity, for the lowest adopted support), and these rules lacked any interest factor as they mostly consisted of an association between the state and city as per the example: Destination = Paranaguá 2999 → UFDESTINATION = PR 2999. Further, since the attributes for abbreviations of state for the same origins and destinations existed, the city consisted of a degree of refinement that brought little benefit at a relatively high cost in the search of interesting rules.

Finally, and in order for the *Apriori* algorithm application to be possible (Agrawal and Srikant, 1994; Liu et al., 1998) regarding the present data, the discretization of numeric attributes, distance (km), and freight cost (R$/t) was necessary. As such, each class was split up based on frequency (Equidepth) because this method, besides giving us good results for numeric attributes, has a good success rate in preventing unbalanced classes. Further, specifically for the distance (km) attribute it was possible to establish an upper limit for the first 500 km, which was intentionally done in accordance with Nazario (2011) and Oliveira (2006); the road freight behavior for grains changes after that limit, diminishing the price growth curve, becoming cheaper per kilometer travelled. Thus, there was a desire for this known behavior to be evidenced by the rules. As such, four intervals were generated for each one of the required attributes for discretization, as per Figure 1 and Figure 2.

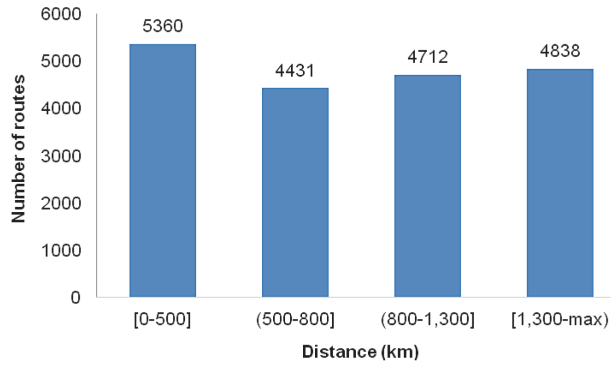

Fig. 1. Discretization Intervals created for the distance (km) attribute

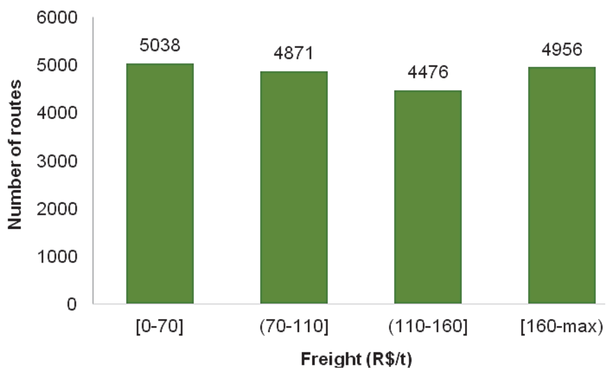

Fig. 2. Discretization Intervals created for the freight cost (R$/t) attribute

Technique application

The application of the *Apriori* algorithm on the data bank was realized using the *Weka* tool (WEKA, 2016) and the version used was 3.7.9. In the Associate section, the confidence parameter value was fixed at 0.7 and initially 0.9 for the support. Since no rule was found, the support was reduced in an interactive manner until the first rules of association were found. This was finally accomplished when the support value reached 0.2 and 10 rules were found. From then on, the support was decremented until it reached a value of 0.01; this is the value that resulted in the greatest number of rules, reaching 2509 rules found by the algorithm. This happens because the support represents how frequent a rule must be in relation to the complete mass of data for it to be recognized by the technique. As such, the lower the restriction, the greater is the chance of the algorithm returning the information.

It is important to note the value of 0.7 selected for the confidence parameter and kept constant during the entire execution of the algorithm, focused on filtering rules with lower values than 0.7. As previously mentioned, confidence represents the strength of the rule, thus the higher it is, the more representative the rule is. A rule with low confidence may represent a very isolated case or even a statistical noise, which was considered uninteresting for this study. According to Han et al. (2012), the minimum limit for confidence must be established by the user resorting to previous knowledge possessed by him about the data and the described scenario. As such, the value of 0.7 was defined after verifying that values lower than this would make the algorithm return many pointless rules in the context of soy and corn transport routes.

The curve shown in Figure 3 describes the growth of the number of rules found, relative to the support value used in each execution of the algorithm.

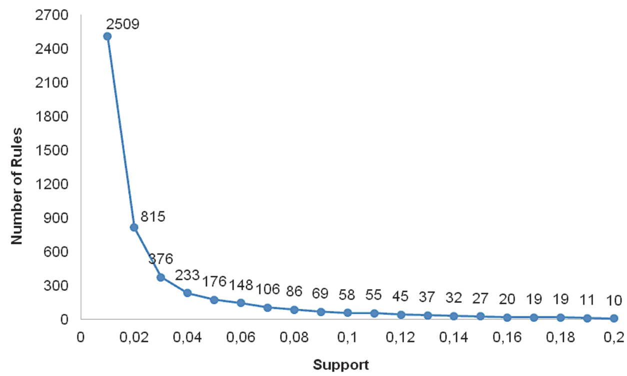

Fig. 3. Amount of rules found x used support figures

Results and Discussion

From the total rules of association recognized by the algorithm during its executions, nine were selected through a process of manual analysis and validated by a specialist from the agricultural freight data bank, for representing interesting and accurate patterns of the area's known scenarios. Table 2

Table 2
Main rules of association selected prior to manual analysis

ID	Support	Confidence	Rule
A	0.10	0.80	UFORIGIN = PR ⇒ UFDESTINATION = PR
B	0.09	0.85	Distance (km) = (1300 max) ⇒ UFORIGIN = MT
C	0.09	0.82	R$/t = (160-max) ⇒ UFORIGIN = MT
D	0.07	0.96	UFDESTINATION = MT ⇒ UFORIGIN = MT
E	0.06	0.77	UFDESTINATION = SC ⇒ PRODUCT = Corn
F	0.03	0.96	UFORIGIN = RS ⇒ UFDESTINATION = RS
G	0.03	0.73	UFDESTINATION = GO ⇒ PRODUCT = Soy
H	0.03	0.76	UFDESTINATION = MA ⇒ PRODUCT = Soy
I	0.03	0.83	UFORIGIN = MT UFDESTINATION = MG ⇒ YEAR = 2015

shows the complete list of selected rules as well as support and confidence values assigned to each of them.

Rule A, the one that has greatest support (0.10) and, as such, greater frequency in the data mass, may be interpreted in a way that shows that grains produced in the state of Paraná are shipped from its main port, the port of Paranaguá, as it is a large grain producing state and has the second biggest soy and corn exporting port in Brazil. The rule has in its predecessor and successor the very same state, respectively, in the UFORIGIN and UFDESTINATION attributes.

Rule B shows that with strong confidence (0.85), if the observation holds the greatest distance of all (maximum of 1300 km), it also presents the state of Mato Grosso (MT) as the freight route origin. That was a rule that stood out since the first sets were generated and may be explained by the very high volume of grains produced in MT, as it is the main soy producing state in Brazil, that need to be forwarded to the ports. However, the Central-West region of Brazil requires long distances to be travelled to connect with the main grain exporting ports located on the coastal regions, especially in the South and South East regions.

Rule C, in fact complements the previous rule, because a long route originating in MT implies a higher freight price. This happens because distance and freight cost have a direct relation.

Rule D is one of the surprises emerging from the analysis. It was immediately clear that the long and expensive routes dominated the state of MT, where this state would always be the origin as this is a production state. However, the same state is the destination and not a coastal one and thus does not have its own port. This point clearly shows the dynamics of internal logistics for the state of MT. The recent fact is that the increase in state capacity for storage has been trying to correct the storage deficit that MT still holds (Oliveira, 2014). Each year, the state has increased its static capacity by about 1 million ton, and by 2015 it had a storage capacity of 33.4 million tons, while the production of grains reached 43.4 million tons (CONAB, 2016). Besides this, another factor which has helped this move within the state is the surge of new intermodal transport routes, fueled by new transportation projects. Mainly, the road and rail terminal of Rondonópolis (MT) that joins MT by rail to the state of São Paulo and to the port of Santos (Oliveira, 2014). Although Rule E has a lower confidence than the previous ones (0.77) but still reveals an interesting pattern, since it shows that if the destination is the state of Santa Catarina (SC) and the grain to be transported is corn. Two important observations arise. The first being that it is possible to confirm that the movement of corn occurs to suppress the demand of one of the main pork and chicken producers in Brazil, who owns one of the biggest pig and chicken herds (Duarte et al., 2015). This characteristic makes SC demand a large volume of corn as its animal rations. The second interpretation is that the port of São Francisco do Sul, located in the northern coast of the state, mostly receives corn and not soy through interstate routes.

Rule F is similar to rule D because it presents the same state as the origin (predecessor) and destination (successor) in the rule. However, this time it refers to the state of Rio Grande do Sul (RS), which is not only a producer state but also has an important port for shipping soy, the Port of Rio Grande. However, it is not possible to state precisely if the destination of the grains is the port or storage silos. Still, it is possible to say that what is produced in RS is, in some way, processed or exported by the same state.

Rule G shows that the state of origin is Goiás (GO), thus the grain is soy. This is a less obvious rule than the previous ones. We know that GO is a producer state, especially of soy, and just like MT it is not on the coast and therefore does not have a port. Due to previous analysis we know that soy production in GO is shipped to the coastal ports. However, if the destination is the same state, the explanation again lies in the storage by silos or in the processing by the grain processing industries. The interesting fact here is that even if the state produces corn, the rule shows that only soy is stored and/or processed in the same state. To corroborate this as per the data from the Brazilian Association of Vegetable Oil Industries (ABIOVE, 2016), the state of Goiás occupies the fourth position in the Brazilian ranking of installed capacity for soy processing (13% of the national capacity), thus crushing around 23.5 thousand tons per day.

Rule H is similar to the previous rule, although its interpretation is different, as the state of Maranhão (MA) has the port of São Luís which exports a large part of its production. As such and in accordance with the rule, the port receives more soy than corn, since a similar area has not been identified for the production of corn.

Finally, Rule I showed the most interesting pattern from our entire analysis. The state of MT as a producer and, as such, the origin of transport routes, has been mentioned several times throughout the current study. But the novelty lays in the state of Minas Gerais (MG) as being the destination for routes beginning in MT. This happens because MG is a state without a coastline and, therefore, without a port and still without a relevant storage capacity, having a static capacity of 8.9 million tons (6% of the national storage capacity) (CONAB, 2016). Even if the state had a significant storage capacity it would not make any sense to move grain to be stored in a state that does not have sufficient capacity for processing/crushing (only 5% of milling capacity, about 9 thousand tons per day) (ABIOVE, 2016) or exporting.

The most important in this state is the fact that Minas Gerais presents a good railway network and has important railway transfer terminals located in the cities of Uberaba, Uberlândia, and Araguari, all part of the region of the mining triangle, that transfers cargo from the road network to the railway network, for shipping to the next destination, which generally is the port of Vitória in the state of Espírito Santo. Further, the rule establishes that the move between MT and the intermodal terminals of MG, occurred with higher intensity in 2015.

Conclusion

Throughout the course of the current study it was possible to verify a few conclusions that are already known by the specialized literature in the area of data mining: a) the data preparation stage is what absorbs most time when executing a project; b) the discretization of attributes directly influences the rules we found and, for a higher success rate, it is necessary to have knowledge about the specific data bank; c) even in case of little knowledge on the data bank, the identification of interesting rules of association was revealed to be a very effective method for greater learning about the data concerned, because even the obvious and frequent patterns give us plenty of information about the behavior of data.

Many patterns and rules were identified for the State of Mato Grosso, due to the volume of routes used and the expressiveness of grain production in that region. The rules go from the fact that the longest and most expensive routes are found in Mato Grosso, until the identification of the State's internal logistics dynamics, since a part of the production is directed to storage or industrial processing in Mato Grosso itself. Further, part of the soy originating from MT also has as its destination the mining triangle, in this case the shipping is done by the existing intermodal road and railway networks that connect the production of grains in MT to the transfer rail terminal of Uberaba or Araguari (MG) and, from there, heads to the Port of Vitória (ES) through the Central Atlantic Railway (FCA).

Finally, the idea of developing a more systemic and automated technique for identifying interesting rules is proposed for future study. A specialist system can also be considered, one that would hold part of the specialized knowledge or expertise in data banks for road transportation of grains with the goal of executing a categorization of the rules supported by a knowledge database modelled with that intent and specific to agricultural freight routes.

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Received September, 8, 2017; accepted for printing October, 30, 2017